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Testing the Predictive Value of Subjective Labour Supply Data

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Abstract

Empirical implementation of labour supply theories is usually based on realized labour market behaviour. This requires strong assumptions about the impact of labour demand. A possibility to avoid these assumptions is to make use of subjective data on desired labour supply. In this paper we investigate whether respondents' answers to survey questions on the desired number of working hours contain additional information on the preferences of the individuals. Using panel data for the Netherlands, we analyze whether deviations between desired hours and actual hours of work help to predict future job changes or changes in hours worked. We use parametric and recently developed nonparametric tests. The results suggest that subjective information on desired working hours are helpful in explaining female labour supply. For males the evidence is mixed.

Keywords: labour supply, subjective data, hypothesis testing, nonparametric methods

JEL Classification: C12,C14,J22

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1. Introduction

The standard neoclassical theory of labour supply is built on the assumption of utility maximization of individuals or households. Facing a certain choice set consisting of attainable combinations of hours worked and earnings, the individuals choose their optimal number of working hours. In this theory labour demand has an important role: it determines the choice sets. Survey data on actual labour market behaviour, however, only reveal actual employment status, earnings, and hours worked, while the individuals' choice sets are not observed. Therefore, in structural empirical models of labour supply, rigorous assumptions with respect to the demand side of the labour market usually have to be made. Traditionally, it is assumed that the individuals can choose any number of working hours, up to a maximum equal to the time endowment. See, for instance, the seminal article of Heckman (1974). This assumption excludes the existence of involuntary unemployment. It also excludes a possible lack of part-time jobs, which forces individuals to choose between not working or working full-time. A large part of the empirical labour supply literature is built on this assumption.

Still, several authors have tested or relaxed this assumption of free choice. Two main strategies can be distinguished. The most common strategy is to incorporate involuntary unemployment or other hours restrictions in the structure of the model, but to use data on actual labour supply behaviour only. For example, Blundell et al. (1987) incorporate involuntary unemployment explicitly, and find that this improves the empirical fit of the model significantly. This type of model has been estimated for various countries. Altonji and Paxson (1988) investigate why changes in preferences have a larger effect on hours for job-changers than for job-stayers, and conclude that restrictions on working hours in the job play a major role. Tummers and Woittiez (1991) and Dickens and Lundberg (1993) explicitly model the probability that jobs with a certain number of working hours are not available. The drawback of all these studies is that actual hours have to identify preferences as well as restrictions. Identification therefore requires auxiliary assumptions, and the question remains to what extent the results are driven by the auxiliary assumptions.

An alternative strategy is to use subjective data on labour supply, representing the desired labour market status. Many surveys on a household or individual level contain data on restrictions on working hours or on the number of hours that an individual would like to work. Biddle (1988) and Ball (1990) use the US Panel Study of Income Dynamics and conclude that restrictions on working hours are important, as the dynamic model for labour supply is rejected for the full sample of workers but accepted for the sample with unrestricted workers only. Kahn and Lang (1991) estimate static models of labour supply on the basis of actual and desired hours in the Canadian Labor Force Survey, and find that the elasticity estimates based upon actual working hours are biased upward.

Subjective data can thus be used to test the traditional labour supply models. They can also be used to identify restrictions in the labour market, by confronting desired with actual hours. Using information on desired and actual working hours in the Finnish Labour Force Survey, Ilmakunnas and Pudney (1990) find that women experience a substantial lack of part-time jobs. On the basis of the British Household Panel Survey, Stewart and Swaffield (1995) find that male manual workers are often overemployed, and explain this from lower bounds on working hours imposed by the firm. Similar findings for Sweden are given in Sacklén (1996). Stratford et al. (1995), on the other hand, find that in the US, overemployment among males is much less common than underemployment. Using the Dutch Socio-Economic Panel, Euwals and van Soest (1996) conclude that there is a lack of part-time jobs for unmarried men and women.

A common criticism to using subjective data is that the reliability of individuals' answers to this type of questions is unclear. It is not guaranteed that the answers reflect optimal behaviour, since the respondents are not penalized for a 'non-optimal answer.' Stratford et al. (1995) and Sacklén (1996) allow explicitly for misclassification of over- and underemployment and find significant misclassification probabilities. They need rather strong assumptions to identify these probabilities, however.

The purpose of this paper is to investigate whether subjective data on labour supply say anything about future labour market adjustment. The null hypothesis is that they do not. We will test this hypothesis by confronting desired labour supply with future changes in job status and actual hours worked. We use the Dutch Socio-Economic Panel, which contains information on both actual and desired working hours for the same individuals in three consecutive years. Under the null hypothesis, the answers to the desired hours questions in year t do not significantly contribute to explaining actual working hours in year t+1. This either means that desired hours contain no information on preferences additional to the information contained in actual hours, or that hours worked are completely determined by demand and individuals are unable to adjust them. The main novelty in this paper is that we look at changes over time using panel data, while the existing studies comparing desired and actual labour supply have focused on single cross-sections.

Non-workers with desired hours equal to zero do not participate in the labour market. Non-workers with positive desired hours are sometimes discouraged, but will usually be looking for a job. It is well-known that job searchers have a larger probability of working twelve months later than other non-workers with similar characteristics. It therefore seems obvious that for non-workers, the null hypothesis that deviations between desired and actual hours of work say nothing about future changes, will be rejected. In the current paper, we do not pursue this issue and focus on those who work in year t.

The remainder of this paper is organized as follows. In section 2 we first present the subjective questions on desired labour supply and the methodology we employ to test whether this desired labour status information can contribute to explaining the future labour market status. In section 3 we describe the data we use. Section 4 contains the results of the tests. Finally, section 5 concludes: subjective information could help to explain labour supply behaviour for women. For men, the evidence is mixed.

2. Survey questions, hypotheses, and tests

We first present the questions on the desired labour market status. Then we describe in general terms the methodology we employ to test whether this information has any effect on the future labour market status.

The questions on actual and desired hours of work which the individuals answer in the October waves of 1987 and 1988, are as follows:

Ia How many hours per week do you work in your job, or jobs?
- *Do not include travelling time to and from your work.*
- *Include overtime only if it is paid.*

Ib Are you satisfied with this number of working hours, or would you prefer to work more or fewer hours per week? Possible answers:

1) I am satisfied with the number of working hours.

2) I prefer to work more.

3) I prefer to work less.

Ic If, in the previous question, you were not satisfied with your number of working hours, how many hours would you like to work then?

The answers to questions Ia to Ic by individual i in year t are denoted by ha_{it}, s_{it}, and hd^*_{it}, respectively. 'Actual hours' ha_{it} and 'desired hours' hd^*_{it} are measured as hours per week. We define 'satisfaction' s_{it} as follows: $s_{it} \equiv 0$ if individual i is satisfied with the number of working hours in period t (answer 1), $s_{it} \equiv -1$ if the individual wants to work less (answer 3) and $s_{it}=+1$ if the individual wants to work more (answer 2). Respondents only answer question Ic when they are not satisfied with the number of working hours reported under Ia. We assume that, for respondents who report to be satisfied with their number of working hours ($s_{it}=0$), desired hours equal actual hours, i.e., $hd^*_{it}=ha_{it}$. Thus '*observed* desired hours' hd_{it} are given by:

$$hd_{it} = I[s_{it}=0]ha_{it} + I[s_{it}\neq 0]hd^*_{it} \tag{1}$$

Here I[A] is the indicator function, with value 1 if A is true and 0 if it is false.

Let y represent the variable referring to future labour market status and let z present information on desired labour supply. We want to find out whether the subjective information in z has any effect on y. We distinguish three possibilities for y:

A. $y = I[ha_{it+1}>0]$;

Thus, y equals 1 if individual i works in t+1 and 0 otherwise.

B. $y = ha_{it+1} - ha_{it}$;

Here y represents the future adjustment of actual hours of work.

C. In the third case y is a dummy indicating whether individual i has changed job between dates t and t+1.

We also distinguish three cases for z, the present subjective information on the desired labour market status:

a. $z = s_{it}$;

In this case we only check whether the answer to question Ib has an effect.

b. $z = hd^{*}_{it} - ha_{it}$;

In this case we restrict attention to the subsample of people who are over- or underemployed ($s_{it} \neq 0$, so $hd_{it} = hd^{*}_{it}$) and investigate whether the answer to question Ic - the size of over- or underemployment - has an effect in addition to the qualitative information that people are under- or overemployed.

c. $z = hd_{it} - ha_{it}$.

Here we want to check whether the difference between present desired hours (using definition (1)) and present actual hours has some effect.

The reason for this distinction is that in several surveys used in the literature, s_{it} is available, but the exact information on hd_{it} is not. See, for example, Stratford et al. (1995) and Sacklén (1996). In case a we analyze the value of s_{it}, the information on over- and underemployment, only. In case b, we analyze whether it is worthwhile to add information on the size of over- and underemployment. Case c leads to a direct test of the value of the complete information.

In addition, let x be a vector of conditioning variables. x will include at least the present number of working hours, ha_{it}, since it is likely that the future status will depend on the present number of actual working hours. In case b we also include s_{it} in x.

Let $P_{y|x,z}$ and $P_{y|x}$ denote the probability distributions of y conditional on (x,z) and on x. We are interested in testing the following hypothesis

$$H_0\colon P_{y|x,z} = P_{y|x}. \tag{2}$$

We shall consider two ways to test (2) for the three variables y (cases A, B and C), and for the three variants a, b and c for the subjective information z. Instead of on (2), the tests will be based on the weaker first moment hypothesis implied by (2):

$$E\{y|x,z\} = E\{y|x\} \tag{3}$$

If y is a binary variable (cases A and C), (2) and (3) are equivalent. If y is not binary (case B), then it is somewhat restrictive to consider conditional means only. For example, z could affect the conditional variance of y (or other features of the conditional distribution) without affecting the conditional mean. In our case, however, we see no economic arguments for this. Moreover, the natural alternative hypothesis relates to the first moment: if the null is violated, then $E\{y|x,z\}-E\{y|x\}$ will have the same sign as z.

Restriction (3) can be tested parametrically and nonparametrically. Several nonparametric tests are available in the literature nowadays. Most of these tests can be viewed as moment tests (m-tests). For instance with

$$g(x,z) \equiv E\{y|x,z\}, \quad f(x) \equiv E\{y|x\} \tag{4}$$

the null hypothesis, $g(x,z)=f(x)$ with probability one in x, implies

$$E\{(y-g(x,z))^2 - (y-f(x))^2\} = 0 \tag{5}$$

Whang and Andrews (1993) used this moment restriction to construct an m-test based upon the sample analogue of (5). To avoid degeneracy of the test statistic under the null hypothesis, they require the sample to be split up randomly into two parts. In order to apply their test, both g and f have to be estimated nonparametrically. Alternative tests, also based on some comparison of the nonparametric estimates g and f, are, for instance, Aït-Sahalia, Bickel and Stoker (1996), Lavergne and Vuong (1995), and Wooldridge (1992). We experimented with the Whang and Andrews test. In our case the outcomes of the test turned out to be very sensitive to the way in which the sample is split. As a consequence, the results are always inconclusive, and we therefore do not report them.

An alternative test for H_0 is based upon nonparametric estimates of g only. For instance, if z is continuous, the null hypothesis implies the following moment restrictions

$$E\{\partial g(x,z)/\partial z\} = 0 \tag{6}$$

The sample analogue of this moment restrictions can be used to construct m-tests, see Rilstone (1991). We investigated this idea in a simulation study, following Rilstone in the construction of the sample analogue. According to the simulations, the performance of the test in our case would be poor: the actual size of the test can be much larger than the nominal size, so that the test tends to overreject. We therefore do not apply this approach.

Third, there are nonparametric tests of H_0 which make use of nonparametric estimates of f only. We shall refer to this type of tests as nonparametric LM-type tests, since, just like parametric LM-tests, one only has to estimate under the null hypothesis. Examples are Bierens (1990), Lewbel (1991), White and Huong (1993) and Fan and Li (1996). The type of test which seems easiest to apply, is based on the following moment restriction, implied by H_0

$$E\{(y - f(x))b(z)\} = 0, \tag{7}$$

where b can be any (suitable) function. In general we will choose b(z)=z. For the future adjustment of actual hours (Case B) this should be a good choice, as one might expect a nonnegative impact of satisfaction s_{it} and desired hours hd_{it}.[2] For the probability of working the next year (case A) and for having a new job the next year (case C) the impact of the subjective data is less obvious, and we also try $b(z)=|z|$.

Simulation experiments with this test suggested that it performs reasonably well for our purposes. Nominal size and actual size were close and results were robust with respect to the choice of bandwidths. The test statistic is obtained from (7) by replacing the expectation by its sample analogue and f by a nonparametric estimate. We use a Kernel estimator with Gaussian kernel for f. The test statistic and its limit distribution under the null are derived by White and Hong (1995). We reproduce the results for the sake of convenience. Let $\hat{m}$ be the sample analogue of the lefthand side of (7). Under the null,

[2] Our strategy therefore is to use tests with power in a relevant direction. We do not use consistent tests which have some power in all directions, but possibly low power in the directions of interest.

$$\sqrt{n}\,\hat{m} \rightarrow_d N(0,\ V\{(y - f(x))(b(z) - E\{b(z)|x\})\}) \tag{8}$$

To estimate the asymptotic variance, a nonparametric estimate of $E\{b(z)|x\}$ is required. Again, we use a kernel estimator with Gaussian kernel.

A common problem when applying nonparametric methods is the choice of the bandwidths, which show up in the two kernel estimators. If one is interested in the results of the nonparametric regressions themselves, cross-validation can be applied, for example, by choosing the bandwidths such that they minimize the appropriate mean square errors. The nonparametric regressions obtained in this way have certain optimality properties. In general these optimality properties do not lead to corresponding optimality characteristics of the nonparametric tests. According to Newey (1994), it is necessary to undersmooth in this type of situation. It is well-known that the results can be sensitive to the choice of the bandwidth. We therefore calculate the test statistics for different choices of the bandwidths, using the optimal bandwidths for the underlying nonparametric regressions as the benchmark. To allow for undersmoothing, we will focus on bandwidths which are fractions of the optimal bandwidths. As we need two nonparametric regressions, namely of $f(x)$ and of $E\{z|x\}$, we vary the bandwidths in two dimensions.

In case b above, when $z = ha_{it} - hd_{it}$, we also include in x the variable s_{it}, and restrict attention to the subsample $s_{it} \neq 0$, so that $hd_{it} = hd^*_{it}$ and $s_{it} = \text{sign}(hd_{it} - ha_{it})$. The moment restriction (7) (with $b(z)=z$) is then rewritten as

$$E\{[y - E\{y|x,\text{sign}(z)\}]z\} = 0 \tag{9}$$

In this case the limit distribution under the null becomes

$$\sqrt{n}\,\hat{m} \rightarrow_d N(0,\ V\{\psi\}) \tag{10}$$

$$\begin{aligned} \psi = {} & (y - E\{y|x,z>0\})(z - E\{z|x\})I[z>0] + \\ & (y - E\{y|x,z<0\})(z - E\{z|x\})I[z<0]. \end{aligned} \tag{11}$$

The major advantage of the nonparametric tests is that, at least theoretically, the possibility of biased results as a consequence of misspecification is avoided. A drawback is that, when the null hypothesis is rejected, it may still be unclear what the effect of z on y actually might be. To find this effect by estimating $E\{y|x,z\}$, it is important to include the appropriate conditioning variables in x. However, already including only a few conditioning variables in x makes nonparametric estimation of $E\{y|x,z\}$ quite hard, if not impossible, with the limited number of available observations. Therefore, our second way to test (3) is a parametric approach. We postulate:

$$E\{y|x,z\} = F(x,z;\theta), \tag{12}$$

with F some known function and with $\theta \in \mathbb{R}^m$ some finite dimensional unknown parameter vector. When y is binary (cases A and C) we model (12) by means of Probit with a single index of the form:

$$x'\theta_x + z'\theta_z, \quad \theta = (\theta_x', \theta_z')'. \tag{13}$$

Testing H_0 then boils down to testing $\theta_z = 0$. This can be done, for instance, by applying a Likelihood Ratio test. When y is continuous (case B) we model (12) by means of a linear regression function similar to (13). Next to actual hours ha_{it}, conditioning variables x will include job characteristics, individual characteristics like age and education level, family characteristics and region dummies.

3. Data

The Dutch Socio-Economic Panel (SEP) is a biannual panel on the household level. It is representative for the Dutch population excluding those in nursing homes etc. It contains several questions on the labour market situation of the individuals. Employed persons answer questions on the characteristics of their job and their employer. Included are also the questions Ia, Ib and Ic of the previous section.

In this paper we will use those individuals who are employed and whose numbers of actual and desired working hours are observed in the October waves of 1987 or 1988.[3]

[3] Due to various reasons like changing definitions and questioning strategy not all waves can be used. For example, in early waves, the questions on desired and actual hours have only been answered by those who changed job since the previous interview.

As we want to analyze the job status and working hours in the next year, we merge both 1987 and 1988 to their next year. We will use two samples: a first one with the individuals who work in year t and who are observed the next year (whether working or not), and a second one only including the individuals who work in both years.

Table 1: sample statistics (working in year t and observed in year t+1)

	Men		**Women**	
	t=1987	**t=1988**	**t=1987**	**t=1988**
# observations	2824	2883	1638	1694
one job	96.8%	96.3%	96.5%	95.5%
salaried employment	92.3%	93.4%	91.4%	92.4%
actual hours ha_{it}				
mean	41.15	40.95	26.70	26.77
stand. dev.	10.31	10.42	13.38	13.58
satisfaction s_{it}				
wants to work less	26.6%	24.0%	19.2%	19.5%
satisfied	68.8%	71.8%	71.6%	72.1%
wants to work more	4.5%	4.2%	9.2%	8.4%
desired hours hd_{it}				
mean	38.99	38.99	25.76	25.87
stand. dev.	9.19	9.61	12.04	12.05
job status year t+1				
not working	4.7%	4.3%	10.8%	9.0%
same job	87.5%	87.4%	81.5%	81.6%
other job	7.8%	8.3%	7.7%	9.4%

Table 1 shows some statistics of the first sample. Individuals who work in year t, but are no longer in the sample in year t+1 (t=1987, 1988), are not included. For each of the subsamples (1987 and 1988, men and women), the attrition is between 8 and 10 percent. This could lead to an attrition bias in the analysis if attrition would be related to job status or hours worked. To get some insight into whether such a relationship exists or not, we compared the sample characteristics in Table 1 with the characteristics of the complete sample, including the respondents not in Table 1, see appendix A. The sample characteristics in the complete sample (see Table A.1) are very similar to those in Table 1. Cross tabulations (Table A.2) of attrition and satisfaction with working hours do not indicate any relation: Likelihood Ratio tests do not reject the null hypothesis of independence. We also consider probit regressions explaining attrition from various variables observed in year t (Table A.3). Some of the included exogenous variables turn out to be significant, but the signs vary and the satisfaction with working hours variable remains insignificant. It therefore seems reasonable to ignore attrition bias in the sequel.

Table 2: sample statistics (working in years t and t+1)

	Men		**Women**	
	t=1987	**t=1988**	**t=1987**	**t=1988**
# observations	2692	2759	1461	1542
one job	96.8%	96.2%	96.3%	95.6%
salaried employment	92.3%	93.3%	91.5%	92.7%
actual hours ha_{it}				
mean	41.46	41.29	27.08	27.28
stand. dev.	10.00	10.09	13.34	13.49
satisfaction s_{it}				
wants to work less	27.0%	24.5%	19.0%	19.5%
satisfied	68.5%	71.5%	71.5%	72.6%
wants to work more	4.5%	4.0%	9.4%	7.8%
desired hours hd_{it}				
mean	39.26	39.25	26.20	26.25
stand. dev.	8.81	9.32	12.03	12.03
actual hours year t+1				
mean	41.44	41.46	27.53	27.59
stand. dev.	9.70	10.03	13.42	13.17

As men and women behave very differently in terms of labour supply, we consider them separately. Female labour force participation, at least in the Netherlands, is substantially lower than male labour force participation. From Table 1 we see that most individuals have one paid job. For those with more than one job, actual and desired hours refer to the total in all jobs. The large majority of the employed are salaried employees. For both men and women, about 70 percent is satisfied with their number of working hours. Most men and women stay in the same job. The fraction of people who stop working is substantially higher for women than for men. There is a difference in realized behaviour between the two years: From October 1987 to October 1988, more individuals became unemployed and less found a new job than from October 1988 to October 1989.[4] Table 2 shows the sample statistics of the second sample, including only those individuals who work in two consecutive years. A large part of our analysis will be based on this sample, as we use the first sample only to analyze the probability of having no job in the next year. Compared to Table 1, average actual working hours in year t increase slightly for all four subsamples. This might be due to the fact that jobs with few working hours are more likely to end. Still, hardly any systematic change is found in the other characteristics. One might expect satisfaction with working hours to have some effect on the probability of having no job the next year, but this effect is not obvious from the tables. We will analyze this in more detail in the next section.

Figure 1 shows nonparametric regressions of ha_{it+1} on ha_{it} and hd_{it}, for t=1987 and 1988 and for men and women. The optimal bandwidths are determined by cross-validation. For t=1987, the regressions are reasonably smooth. For t=1988, the optimal bandwidth for men seems to lead to undersmoothing, while the optimal bandwidth for women seems to oversmooth. For women there seems to be a positive relation between next year's actual hours ha_{it+1} and desired hours hd_t. For men this is less clear.

Figure 2 presents nonparametric regressions of ha_{it+1} on hd_{it} for particular values of ha_{it}. The plotted uniform confidence bands are projections of the uniform confidence bands of the nonparametric regressions of figure 1, which are not presented there to avoid messy pictures. Taking the shape of the uniform confidence bands into account, the graphs of figure 2 seem to indicate that desired hours hd_{it} indeed might have an effect on actual hours next year ha_{it+1}. In the next section we shall test this formally.

4. Results

In this section we present the results of our tests using the methodology of section 2. For each of the three cases A, B and C (the different future variables y) we first describe the data further by cross tabulating of y and s_{it}, testing at the same time the hypothesis of independence between y and s_{it}. Then we present for each of the cases A, B and C the results of the nonparametric and parametric tests for the cases a, b and c (different subjective information variables z), including also conditioning variables x.

[4] This is in line with aggregate data for the Netherlands: unemployment fell and participation rose (SZW, 1991).

Table 3: cross tabulation for employment status

Men	**t=1987**			**t=1988**		
wants to work:	less	satisfied	more	less	satisfied	more
work at t+1	96.5%	94.9%	94.5%	97.4%	95.4%	91.7%
no work at t+1	3.5%	5.1%	5.5%	2.6%	4.6%	8.3%
# observations	752	1944	128	693	2069	121
LR test	3.652 (prob.=0.161)			9.900 (prob=0.007)		
Women	**t=1987**			**t=1988**		
wants to work:	less	satisfied	more	less	satisfied	more
work at t+1	88.2%	89.2%	91.4%	91.2%	91.7%	84.6%
no work at t+1	11.8%	10.8%	8.6%	8.8%	8.3%	15.4%
# observations	315	1172	151	330	1221	143
LR test	1.089 (prob=0.580)			6.813 (prob=0.033)		

Note: The LR test is a Likelihood Ratio test on independence of row and column events. Under the null hypothesis of independence they follow a χ^2_4 distribution

4.1 Testing for an effect on employment status (case A)

We first analyze the effect of the subjective information in z (in the form of a, b, or c) on $y=I[ha_{it+1}>0]$, a dummy indicating whether an individual works in the next year or not.

First, we present a cross tabulation between $y=I[ha_{it+1}>0]$ and the subjective variable s_{it}, see Table 3. It turns out that men who want to work more have a lower probability to work in the next year than other men. For women we find this same result for the transitions between 1988 and 1989. If the decision to stop working is voluntary, we would expect that individuals who want to work less have a higher probability to stop than individuals who are satisfied or want to work more. This result is only found for women in 1988, and it is insignificant, since the null of independence between satisfaction $z=s_{it}$ and employment status in year t+1, cannot be rejected in this case. The reason for this finding may be that individuals who want to work more, generally have jobs with a low number of actual working hours. These jobs might be less stable and more likely to end. In other words, the cross tabulation of Table 3 has the drawback that the possible effect of actual working hours is not controlled for. For that purpose, we need to consider the nonparametric and parametric tests.

Table 4: nonparametric LM-type test for staying employed

Men	**t=1987**	**t=1988**
a: satisfaction s_{it}		
optimal bandwidth	(2.4 , 1.9)	(5.3 , 1.8)
range test-statistic	[0.66 , 0.79]	[-1.27 , -1.00]
b: desired hours hd_{it}, conditional		
optimal bandwidth	(5.3 , 2.4)	(9.9 , 4.3)
range test-statistic	[1.22 , 1.86]	[-0.51 , 0.96]
c: desired hours hd_{it}, unconditional		
optimal bandwidth	(2.4 , 1.5)	(1.2 , 1.6)
range test-statistic	[0.64 , 2.37]	[-0.67 , 0.50]
Women	**t=1987**	**t=1988**
a: satisfaction s_{it}		
optimal bandwidth	(11.2 , 2.3)	(2.6 , 1.8)
range test-statistic	[2.40 , 3.26]	[0.64 , 0.88]
b: desired hours hd_{it}, conditional		
optimal bandwidth	(∞ , 3.2)	(8.5 , 4.7)
range test-statistic	[0.53 , 0.54]	[-1.33 , -0.32]
c: desired hours hd_{it}, unconditional		
optimal bandwidth	(11.2 , 0.8)	(2.6 , 2.0)
range test-statistic	[3.01 , 3.87]	[-0.67 , 0.02]

Note: the first optimal bandwidth concerns the nonparametric regression $f(x)=E\{y|x\}$, the second concerns the nonparametric regression $E\{b(z)|x\}$. For an optimal bandwidth of ∞, see footnote 3. The test statistic refers to the t-value of the estimated moment.

Table 4 shows the realizations of the nonparametric tests for the three possibilities a, b and c for z. In each case, two nonparametric regressions are required (see section 2). The optimal bandwidths for these are determined by cross validation, based on minimizing the sum of squared residuals. In order to undersmooth, the test statistics are then calculated using fractions of the optimal bandwidths. The choice and range of these fractions are based on a small simulation study.[5] The Table shows the minimum and maximum values of the test statistics and the bandwidths for which these are attained.

[5] In case of $f(x)=E\{y|x\}$ we use as fractions of the optimal bandwidths 1.0, 0.8, 0.6, 0.4, 0.2, 0.1, 0.05 and 0.01. As the test-statistic turns out to be insensitive for the choice of the bandwidth of $E\{b(z)|x\}$, we use as fractions 1.0, 0.6 and 0.2. In case the optimal bandwidth is very large (larger than 100), we do not vary the bandwidth in that dimension, but take the average of the corresponding endogenous variable as the nonparametric regression. We denote this by choosing ∞ for the optimal bandwidth.

Table 4 is based on the choice b(z)=z and shows that in most cases the hypothesis that z has no effect on $y=I[ha_{it+1}>0]$, cannot be rejected. There are two exceptions for women in 1987 ($z=s_{it}$ and $z=hd_{it}-ha_{it}$). In one case the result depends on the bandwidth (men in 1987, $z=hd_{it}-ha_{it}$) implying that the test is inconclusive. So from this test we can conclude that the subjective data is not informative for men, while for women the result is unclear. From Table 4 we also learn that the results for 1988 are a bit curious. From the interpretation of the subjective data as an indicator for preferences, one would expect that individuals who want to work less (more) have a lower (higher) probability to be working the next year. This should lead to a nonnegative test statistic. Still for several cases the test statistic is negative. An possible explanation is that individuals who are dissatisfied with their working hours have a larger probability to stop working. This fits more to the choice $b(z)=|z|$ for cases a and b. We tested this, but only for the women of 1988 this lead to significant results. Another explanation for the opposite results for the women of 1987 and 1988 might be spurious correlation. To get more insight on this, we turn to the parametric results.

Table 5 presents a summary of the parametric testing and estimation results based on a probit model, containing conditioning variables like individual and job characteristics. The results of the complete model for case c are given in Table B.1 of appendix B. For the women the results from the parametric tests for 1987 are in line with the interpretation of the subjective data. The women who want to work less drive the significance of the results. For 1988 also, the probability of working the next year is significantly lower for the women who want to work less. But for both men and women in 1988, the signs of the parameter estimates for the individuals who want to work more are opposite to those in 1987. And although only for case b of the men this parameter is significantly negative, this opposite result for seems remarkable. As the nonparametric test also indicated this result, it might be that for this case we are not able to include all relevant characteristics.

For men, we get one significant result, based on a sample of 110 men who want to work more. Thus for men the subjective data does not contain information on the probability that they are still working the next year. For women we get significant results for both 1987 and 1988. In particular, the fact that the women who want to work less have a significantly lower probability to be working the next year is consistent with the interpretation of subjective data as an indicator for preference.

Table 5: parametric test for staying employed

Men	**t=1987**		**t=1988**	
	parameter	stand.err.	parameter	stand.err.
a: satisfaction s_{it}				
dummy less	0.045	(0.121)	0.025	(0.133)
dummy more	0.238	(0.227)	-0.069	(0.210)
test-statistic (critical value)	1.25	(5.99)	0.15	(5.99)
b: desired hours hd_{it}, conditional				
dummy less*$\|hd_{it}-ha_{it}\|$	-0.031	(0.023)	-0.015	(0.027)
dummy more*$\|hd_{it}-ha_{it}\|$	-0.002	(0.039)	-0.197	(0.098)
test statistic (critical value)	1.66	(5.99)	8.00	(5.99)
c: desired hours hd_{it}, unconditional				
dummy less	0.091	(0.191)	0.013	(0.213)
dummy less*$\|hd_{it}-ha_{it}\|$	-0.005	(0.016)	0.001	(0.019)
dummy more	0.126	(0.364)	0.258	(0.350)
dummy more*$\|hd_{it}-ha_{it}\|$	0.010	(0.026)	-0.027	(0.021)
test statistic (critical value)	1.51	(9.49)	1.65	(9.49)

Women	**t=1987**		**t=1988**	
	parameter	stand.err.	parameter	stand.err.
a: satisfaction s_{it}				
dummy less	-0.229	(0.124)	-0.289	(0.127)
dummy more	0.294	(0.170)	-0.153	(0.150)
test-statistic (critical value)	6.74	(5.99)	5.82	(5.99)
b: desired hours hd_{it}, conditional				
dummy less*$\|hd_{it}-ha_{it}\|$	-0.044	(0.019)	-0.055	(0.023)
dummy more*$\|hd_{it}-ha_{it}\|$	0.001	(0.031)	-0.024	(0.026)
test statistic (critical value)	5.14	(5.99)	6.78	(5.99)
c: desired hours hd_{it}, unconditional				
dummy less	0.120	(0.194)	0.043	(0.208)
dummy less*$\|hd_{it}-ha_{it}\|$	-0.036	(0.015)	-0.037	(0.018)
dummy more	0.486	(0.307)	0.209	(0.284)
dummy more*$\|hd_{it}-ha_{it}\|$	-0.015	(0.022)	-0.027	(0.018)
test statistic (critical value)	12.98	(9.49)	12.32	(9.49)

Note: the test-statistic refers to the Likelihood Ratio test for which the critical values at a five percent significance level are χ^2_2 = 5.99 and χ^2_4 = 9.49. Estimates of the conditioning variables like individual and job characteristics are not reported in the table.

Table 6: cross tabulation for adjustment of working hours

Men	**t=1987**			**t=1988**		
wants to work:	less	satisfied	more	less	satisfied	more
ha(t+1)-ha(t)<0	32.9%	23.2%	14.1%	29.2%	22.6%	21.6%
ha(t+1)-ha(t)=0	49.5%	52.7%	43.0%	52.0%	53.1%	40.5%
ha(t+1)-ha(t)>0	17.6%	24.1%	43.0%	18.1%	24.3%	37.8%
# observations	726	1845	121	675	1973	111
LR test	56.121 (prob=0.000)			27.872 (prob=0.000)		
Women	**t=1987**			**t=1988**		
wants to work:	less	satisfied	more	less	satisfied	more
ha(t+1)-ha(t)<0	34.9%	22.7%	13.8%	36.9%	21.0%	13.2%
ha(t+1)-ha(t)=0	44.6%	53.0%	34.8%	44.9%	53.6%	35.5%
ha(t+1)-ha(t)>0	20.5%	24.3%	51.5%	18.3%	25.5%	51.2%
# observations	278	1045	138	301	1120	121
LR test	61.920 (prob=0.000)			70.020 (prob=0.000)		

Note: The LR test is a Likelihood Ratio test on independence of row and column events. Under the null hypothesis of independence they follow a χ^2_4 distribution.

4.2 Testing for an effect on future actual hours of work (case B)

In this subsection we analyze the effect of the subjective information in z (in the form of cases a, b, or c) on $y=ha_{it+1}-ha_{it}$, the change in actual hours.

In Table 6 we cross tabulate satisfaction s_{it} and the sign of the change in actual hours y. This Table shows that satisfaction with working hours has a clear impact in the expected direction on the adjustment of hours over time. This impact is also significant: for all four subsamples, Likelihood Ratio tests strongly reject the null hypothesis of independence. Again however, these results do not control for actual working hours in year t. For example, part-time workers may more often want to increase their working hours than full-time workers. If part-time workers also have a larger chance to increase their working hours, this may lead to spurious correlation. Moreover, there is no reason why we should only consider the direction of the adjustment, and not the actual size of the change in hours worked. We observe how many hours individuals adjust, and using this will probably lead to more powerful tests. For that reason we again turn to the nonparametric and parametric tests.

Table 7: nonparametric LM-type test for adjustment of actual hours

Men	**t=1987**	**t=1988**
a: satisfaction s_{it}		
optimal bandwidth	(3.9 , 1.8)	(4.1 , 1.7)
range test-statistic	[0.24 , 1.31]	[0.54 , 1.27]
b: desired hours hd_{it}, conditional		
optimal bandwidth	(9.2 , 3.5)	(9.1 , 3.3)
range test-statistic	[3.01 , 7.71]	[3.16 , 6.18]
c: desired hours hd_{it}, unconditional		
optimal bandwidth	(2.2 , 1.6)	(2.2 , 1.6)
range test-statistic	[1.43 , 3.05]	[0.83 , 2.80]
Women	**t=1987**	**t=1988**
a: satisfaction s_{it}		
optimal bandwidth	(8.2 , 2.4)	(8.0 , 2.2)
range test-statistic	[3.03 , 4.06]	[3.92 , 5.21]
b: desired hours hd_{it}, conditional		
optimal bandwidth	(9.4 , 3.2)	(7.7 , 4.7)
range test-statistic	[3.82 , 4.29]	[3.66 , 4.97]
c: desired hours hd_{it}, unconditional		
optimal bandwidth	(2.3 , 1.9)	(2.9 , 2.0)
range test-statistic	[2.22 , 4.19]	[3.73 , 4.82]

Note: the first optimal bandwidth concerns the nonparametric regression f(x)=E{y|x}, the second concerns the nonparametric regression E{b(z)|x}. For an optimal bandwidth of ∞, see footnote 3. The test statistic refers to the t-value of the estimated moment.

Table 7 presents the nonparametric testing results for the choice b(z)=z, following the same procedure as in the previous subsection. For women, we find that the null is rejected in all three cases. Apparently, women tend to adjust their working hours if they deviate from their optimum number. Both the satisfaction variable and the actual deviations between desired and actual hours are helpful to predict changes in actual hours. For men, the results are not so clear. For the subsamples of those men who want to work more or less (case b), we find that desired hours contribute significantly to explaining changes in actual hours. But the information on whether or not a man is satisfied with his actual number of working hours, does not contribute (case a). If we look at the impact of desired hours for the sample as a whole (case c), the test result depends on the chosen bandwidths so that the test is inconclusive.

Table 8: parametric test for adjustment of working hours

Men	**t=1987**		**t=1988**	
	parameter	stand.err.	parameter	stand.err.
a: satisfaction s_{it}				
dummy less	0.042	(0.328)	0.202	(0.298)
dummy more	0.640	(0.831)	0.870	(0.872)
test-statistic (critical value)	0.62	(5.99)	1.35	(5.99)
b: desired hours hd_{it}, conditional				
dummy less*$\|hd_{it}-ha_{it}\|$	-0.211	(0.068)	-0.181	(0.075)
dummy more*$\|hd_{it}-ha_{it}\|$	0.261	(0.118)	0.271	(0.120)
test statistic (critical value)	14.52	(5.99)	10.92	(5.99)
c: desired hours hd_{it}, unconditional				
dummy less	0.684	(0.608)	1.128	(0.530)
dummy less*$\|hd_{it}-ha_{it}\|$	-0.074	(0.068)	-0.102	(0.066)
dummy more	-0.061	(1.019)	-1.322	(1.041)
dummy more*$\|hd_{it}-ha_{it}\|$	0.081	(0.108)	0.234	(0.126)
test statistic (critical value)	2.65	(9.49)	8.76	(9.49)

Women	**t=1987**		**t=1988**	
	parameter	stand.err.	parameter	stand.err.
a: satisfaction s_{it}				
dummy less	0.012	(0.524)	-0.246	(0.472)
dummy more	1.581	(0.676)	3.248	(0.667)
test-statistic (critical value)	5.48	(5.99)	24.26	(5.99)
b: desired hours hd_{it}, conditional				
dummy less*$\|hd_{it}-ha_{it}\|$	-0.195	(0.094)	-0.269	(0.093)
dummy more*$\|hd_{it}-ha_{it}\|$	0.299	(0.106)	0.589	(0.126)
test statistic (critical value)	12.26	(5.99)	30.22	(5.99)
c: desired hours hd_{it}, unconditional				
dummy less	0.352	(0.844)	0.545	(0.729)
dummy less*$\|hd_{it}-ha_{it}\|$	-0.041	(0.071)	-0.101	(0.064)
dummy more	-0.847	(1.214)	-3.074	(1.185)
dummy more*$\|hd_{it}-ha_{it}\|$	0.230	(0.095)	0.568	(0.088)
test statistic (critical value)	11.65	(9.49)	68.66	(9.49)

Note: the test-statistic refers to the Wald test for which the critical values at a five percent significance level are χ^2_2 = 5.99 and χ^2_4 = 9.49. Estimates of conditioning variables like individual and job characteristics are not reported in the table.

Table 8 presents the parametric analogues to Table 7. The results of the complete model for case c are presented in Table B.2 of appendix B. The conclusions are similar to those in Table 7 and all significant parameters have the sign which is consistent with the idea that the subjective data contains information on the preferences of the individuals. For women, the significance levels are much higher in 1988 than in 1987, and for $z=s_{it}$ the null is not rejected. For men, we find significant results only if we consider the impact of deviations between desired and actual hours in the subsamples of those who want to work less or more. The overall conclusion is that the evidence that subjective data on desired labour supply are helpful to predict changes in actual hours is quite strong, and that the impact of the subjective data is consistent with the idea that it contains information on the preferences of the individuals.

Table 9: cross tabulation for having a new job

Men	**t=1987**			**t=1988**		
wants to work:	less	satisfied	more	less	satisfied	more
new job at t+1	7.9%	8.0%	13.2%	8.5%	8.5%	13.8%
same job at t+1	92.1%	92.0%	86.8%	91.5%	91.5%	86.2%
# observations	720	1834	121	674	1966	109
LR test	3.633 (prob=0.163)			3.190 (prob=0.203)		
Women	**t=1987**			**t=1988**		
wants to work:	less	satisfied	more	less	satisfied	more
new job at t+1	7.3%	8.3%	14.4%	9.7%	9.8%	17.4%
same job at t+1	92.7%	91.7%	85.6%	90.3%	90.2%	82.6%
# observations	275	1040	138	299	1113	121
LR test	5.932 (prob=0.052)			5.967 (prob=0.051)		

Note: The LR test is a Likelihood Ratio test on independence of row and column events. Under the null hypothesis of independence they follow a χ^2_4 distribution

4.3 Testing for an effect on change of job (case C)

In this section y is defined as a dummy variable equal to 1 if the individual changes his or her main job between dates t and t+1. The question is again whether the subjective information on desired hours of work has any effect on y.

Table 10: nonparametric LM-type test for changing job

Men	**t=1987**	**t=1988**
a: satisfaction s_{it}		
optimal bandwidth	(1.3 , 1.8)	(3.8 , 1.7)
range test-statistic	[-0.50 , -0.41]	[0.21 , 0.42]
b: desired hours hd_{it}, conditional		
optimal bandwidth	(1.2 , 3.4)	(8.5 , 3.5)
range test-statistic	[0.46 , 0.69]	[-0.04 , 0.39]
c: desired hours hd_{it}, unconditional		
optimal bandwidth	(1.3 , 1.6)	(3.8 , 1.6)
range test-statistic	[-1.58 , -0.18]	[-1.04 , 0.24]

Women	**t=1987**	**t=1988**
a: satisfaction s_{it}		
optimal bandwidth	(4.1 , 2.4)	(3.0 , 2.2)
range test-statistic	[2.66 , 2.97]	[2.18 , 2.37]
b: desired hours hd_{it}, conditional		
optimal bandwidth	(∞ , 3.2)	(∞ , 4.7)
range test-statistic	[2.39 , 2.56]	[3.65 , 3.68]
c: desired hours hd_{it}, unconditional		
optimal bandwidth	(4.1 , 1.9)	(2.2 , 2.0)
range test-statistic	[2.77 , 4.31]	[2.80 , 4.12]

Note: the first optimal bandwidth concerns the nonparametric regression f(x)=E{y|x}, the second concerns the nonparametric regression E{b(z)|x}. For an optimal bandwidth of ∞, see footnote 3. The test statistic refers to the t-value of the estimates moment.

Table 9 presents a cross tabulation of satisfaction s_{it} and having a new job y. It shows that men and women who want to work more, have a higher probability to have a new job the next year. For men, the difference is insignificant. For women, the significance probability is just over 5%. These tables, however, may be misleading since they do not control for actual hours, which may be correlated with job changes as well as satisfaction with hours. Therefore we turn again to the nonparametric tests.

Table 10 contains the results of the nonparametric tests for the choice b(z)=z, obtained in a similar way as in the previous subsections. In this case the choice of b(z) is even less obvious as in subsection 4.1, as there is not economic reason why the probability of changing job should be monotonically increasing or decreasing in the subjective data.

Therefore we also tried b(z)=|z| for cases a and b. As this gave only insignificant results, we concentrate on the results for b(z)=z. The differences between the results for males and females are obvious: for men, the information on the desired labour status does not contribute to explaining job changes at all. For women, on the contrary, we always reject the null hypothesis of no effect.

As the significant results for the nonparametric test for women might be a result of spurious correlation, we turn to the parametric results. Table 11 gives the probit estimates and Table B.3 of appendix B gives the complete results of case c. For males, the parametric tests confirm the conclusion of no effect of the desired labour status. For women, however, the parametric test results in all but one case lead to the opposite conclusion as in case of their nonparametric analogues: the subjective variables are now jointly insignificant. Thus the nonparametric tests which only condition on actual hours suggest that desired labour supply information helps to explain females' job changes. The parametric test results, however, show that this effect disappears when additional conditioning variables are included. Table B.3 shows that particularly important are age and having more then one job. For individuals who have more than one job, a change in job also occurs when the individual give up his or her most important job. Overall we conclude that the subjective information does not have an effect on changing job.

5. Summary and Conclusions

In the empirical literature on labour supply, subjective data on the desired labour status are used to test or avoid the traditional assumption that actual hours can be chosen freely. A common criticism against the use of such data is that it is unclear how reliable individuals' answer to these subjective questions are. If answers to subjective questions on the desired labour status do not contain information on the preferences of the individuals, they should not have any predictive value for next year's labour market status. This is basically the hypothesis tested in this paper.

We use the Dutch Socio-Economic Panel, which contains information on both actual and desired working hours for the same individuals in three consecutive years. The first question we consider refers to whether people are satisfied with their working hours, want to work less, or want to work more. The second subjective question refers to desired hours, for those who are not satisfied with their actual hours of work.

Table 11: parametric test for changing job

Men	**t=1987**		**t=1988**	
	parameter	stand.err.	parameter	stand.err.
a: satisfaction s_{it}				
dummy less	0.138	(0.091)	0.121	(0.089)
dummy more	0.123	(0.173)	0.087	(0.172)
test-statistic (critical value)	2.59	(5.99)	1.99	(5.99)
b: desired hours hd_{it}, conditional				
dummy less*$\|hd_{it}-ha_{it}\|$	0.029	(0.018)	0.023	(0.014)
dummy more*$\|hd_{it}-ha_{it}\|$	0.032	(0.025)	0.057	(0.047)
test statistic (critical value)	4.14	(5.99)	3.88	(5.99)
c: desired hours hd_{it}, unconditional				
dummy less	-0.009	(0.141)	0.023	(0.134)
dummy less*$\|hd_{it}-ha_{it}\|$	0.018	(0.013)	0.011	(0.011)
dummy more	-0.185	(0.281)	-0.352	(0.308)
dummy more*$\|hd_{it}-ha_{it}\|$	0.029	(0.020)	0.043	(0.024)
test statistic (critical value)	6.33	(9.49)	6.02	(9.49)

Women	**t=1987**		**t=1988**	
	parameter	stand.err.	parameter	stand.err.
a: satisfaction s_{it}				
dummy less	0.086	(0.156)	0.110	(0.132)
dummy more	0.188	(0.174)	0.282	(0.165)
test-statistic (critical value)	1.41	(5.99)	8.59	(5.99)
b: desired hours hd_{it}, conditional				
dummy less*$\|hd_{it}-ha_{it}\|$	0.015	(0.030)	0.001	(0.030)
dummy more*$\|hd_{it}-ha_{it}\|$	0.013	(0.040)	0.064	(0.037)
test statistic (critical value)	0.34	(5.99)	3.18	(5.99)
c: desired hours hd_{it}, unconditional				
dummy less	-0.053	(0.262)	0.254	(0.218)
dummy less*$\|hd_{it}-ha_{it}\|$	0.014	(0.023)	-0.020	(0.023)
dummy more	-0.228	(0.317)	-0.287	(0.331)
dummy more*$\|hd_{it}-ha_{it}\|$	0.037	(0.022)	0.046	(0.022)
test statistic (critical value)	4.44	(9.49)	8.59	(9.49)

Note: the test-statistic refers to the Likelihood Ratio test for which the critical values at a five percent significance level are $\chi^2_2 = 5.99$ and $\chi^2_4 = 9.49$.

Simple cross tabulations provide a description of the data used. In a number of cases they reveal significant correlations between actual changes in the labour market status and the desired status. However, these tests do not take account of possible spurious correlation due to, for example, current actual hours of work. To include conditioning variables, we turn to alternative tests.

To avoid the possibility of bias as a consequence of misspecification, we use non-parametric tests, based upon moment restrictions that should be satisfied under the null hypothesis. A practical implementation of such tests only makes sense if the number of included conditioning variables is small. Therefore, in addition to these nonparametric tests, we perform parametric tests to include additional conditioning variables.

There are three future events we consider: A: employment status (working or not), B: actual hours worked for those who continue working, and C: whether or not someone changes job for those who continues to working. For men we get mixed results. For the employment status and change of job, the null is not rejected. Only for the future actual hours we get significant results for the subgroups of men who are dissatisfied with their working hours. Our results suggest that more information is contained in the magnitude of the deviations between desired and actual hours than in the mere fact whether someone is over- or underemployed. This is surprising, since simulation studies in Sacklén (1996) suggest that information on whether someone is over- or underemployed is helpful for estimating a labour supply model, but that the exact information on desired hours adds little to this.

As there is not very much variation in the working hours of men, and a substantial part of the dissatisfied wants a small reduction of working hours from 40 to 38 or 36 hours per week, the power of the tests over the whole sample might be small. So we find only weak evidence that the subjective data contains information on the preferences of men.

For women, the results are stronger. Both nonparametric and parametric tests give that the subjective data has a significant impact on the employment status. Specially women who want to work less have a smaller probability to be employed the next year. Furthermore the results for future employment status are strongly significant and consistent with the interpretation that the subjective data contain information on the preferences. Only for the probability of changing job the impact of the subjective data turns out to be insignificant.

The existing literature comparing desired and actual hours is based on cross-section information. Conclusions on the value of information on desired hours are drawn in the framework of a structural labour supply model, and thus require additional assumptions. Here, we have avoided relying on such a framework and have used panel data on actual adjustments to replace the additional assumptions. Overall our nonparametric and parametric tests provide evidence that for women the subjective data on preferred labour supply contains valuable information on the preferences. This can be seen as evidence in favour of the studies which have incorporated this type of information in structural labour supply models. For men, however, the evidence is less convincing, and the value of desired hours information for modelling labour supply is less clear.

References

Altonji, J. and C. Paxson (1988), "Labor Supply, Hours Constraints and Job Mobility", *Journal of Human Resources*, Vol. 27, pp. 256-278.

Aït-Sahalia, Y., P. Bickel and T. Stoker (1996), "Goodness-of-fit tests for regression using kernel methods", working paper, M.I.T.

Ball L. (1990), "Intertemporal Substitution and Constraints on Labor Supply: Evidence from Panel Data", *Economic Inquiry,* Vol. 28, pp. 706-724.

Biddle J. (1988), "Intertemporal Substitution and Hours Restrictions", *The Review of Economics and Statistics*, Vol. 70, pp. 347-351.

Bierens, H. (1990), "A consistent conditional moment test of functional form", *Econometrica*, Vol. 58, No. 6, pp. 1443-1458.

Blundell, R., J. Ham and C. Meghir (1987), "Unemployment and female labour supply", *The Economic Journal (conference papers),* Vol. 97, pp. 44-64.

Charlier, E., B. Melenberg and A. Van Soest (1995), "A smoothed maximum score estimator for the binary choice panel data model with an application to labour force participation", *Statistica Neerlandica*, Vol. 49, nr. 3, pp. 324-342.

Dickens, W. and S. Lundberg (1993), "Hours restrictions and labor supply", *International Economic Review*, Vol. 34, pp. 169-192.

Euwals, R. and A. Van Soest (1996), "Desired and actual labour supply of unmarried men and women in the Netherlands", CentER discussion paper, Nr. 9623, Tilburg.

Heckman, J.J. (1974), "Shadow prices, market wages and labor supply", *Econometrica*, Vol. 42, pp. 679-94.

Ilmakunnas, S. and S. Pudney (1990), "A model of female labour supply in the presence of hours restrictions", *Journal of Public Economics*, Vol. 41, pp. 183-210.

Kahn, S. and K. Lang (1991), "The Effect of hours Constraints on Labor Supply Estimates", *The Review of Economics and Statistics*, Vol. 73, pp. 605-611.

Konakov, V. and V. Piterbarg (1984), "On the convergence rate of maximal deviation distribution for kernel regression estimates", *Journal of Multivariate Analysis,* Vol. 15, pp. 279-294.

Lavergne, P. and Q. Vuong (1995), "Nonparametric significance testing", working paper, INRA, Toulouse.

Lewbell, A. (1991), "Applied consistent tests of nonparametric regression and density restrictions", working paper, Brandeis University.

Newey, W. (1994), "Kernel estimation of partial means and a general variance estimator", *Econometric Theory*, Vol. 10, pp. 233-253.

Rilstone, P. (1991), "Nonparametric hypothesis testing with parametric rates of convergence", *International Economic Review*, Vol. 31, No. 1, pp. 209-227.

Sacklén, H. (1996), "Essays on empirical models of labor supply", *Economic Studies* 27, Department of Economics, Uppsala University.

Samarov, A. (1993), "Exploring regression structure using nonparametric functional estimation", *Journal of the American Statistical Association*, Vol. 88, pp. 836-847.

Stewart, M. and J. Swaffield (1995), "Constraints on Desired Hours, Trade Unions and the Length of the Working Week for British Men", working paper, CEPR.

Stratford, M., K. Smith Conway, and G. Ferrier (1995), "A switching frontier model for imperfect sample separation information: with an application to labor supply", *International Economic Review*, Vol. 36, pp. 503-527.

SZW (1991), *Rapportage Arbeidsmarkt 1991*, Ministery of Social Affairs and Employment, The Hague.

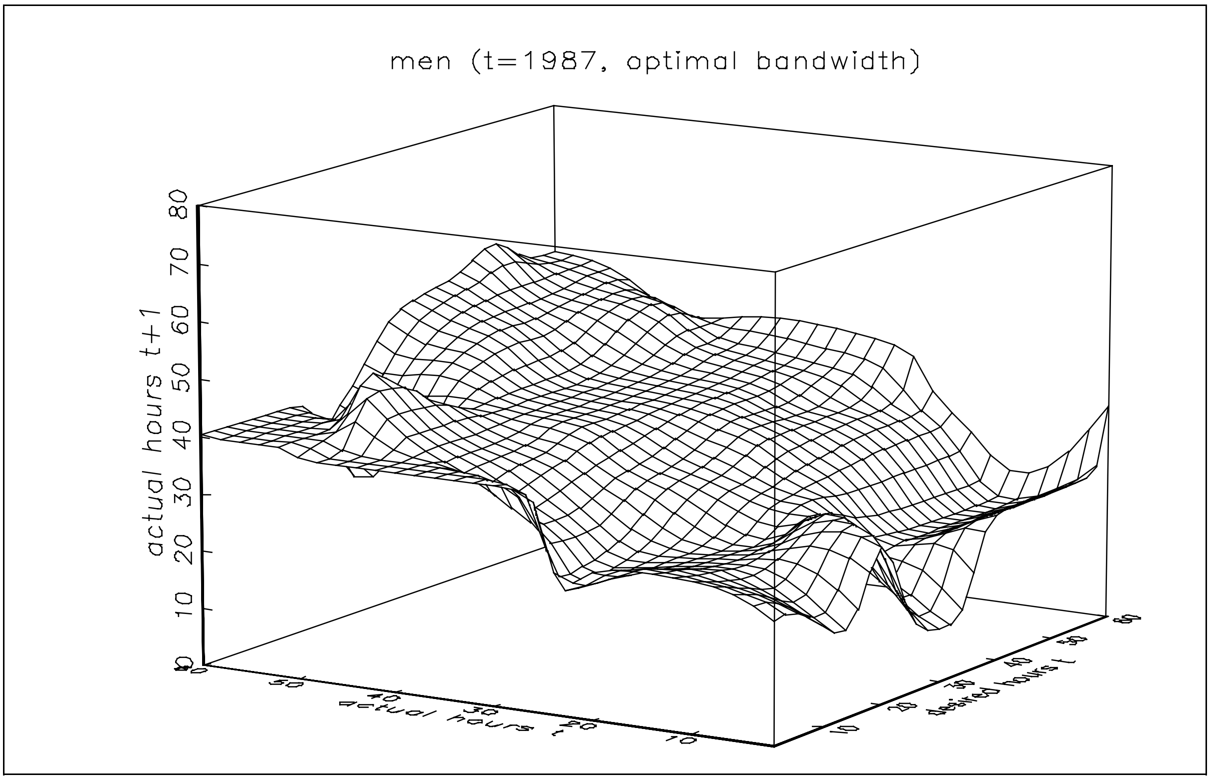
Tummers, M. and I. Woittiez (1991), "A Simultaneous Wage and Labor Supply Model with Hours Restrictions", *Journal of Human Resources*, Vol. 26, pp. 393-423.

Whang, Y. and D. Andrews (1993), "Tests of specification for parametric and semiparametric models", *Journal of Econometrics*, Vol. 57, pp. 277-318.

White, H. and Y. Hong (1993), "M-testing using finite and infinite dimensional parameter estimators", mimeo, University of California, San Diego.

Wooldridge, J. (1992), "A test for functional form against nonparametric alternatives", *Econometric Theory*, Vol. 8, pp. 452-475.

Figure 1a: Nonparametric regression for men, 1987 and 1988



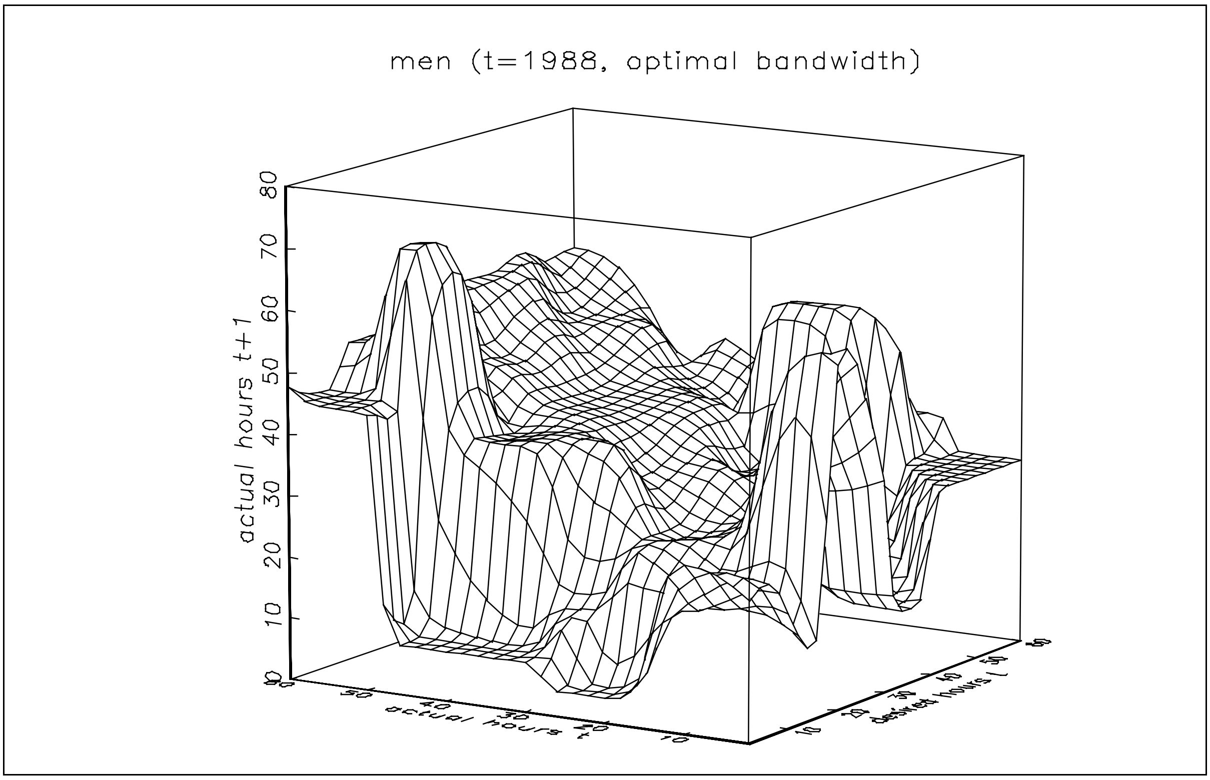
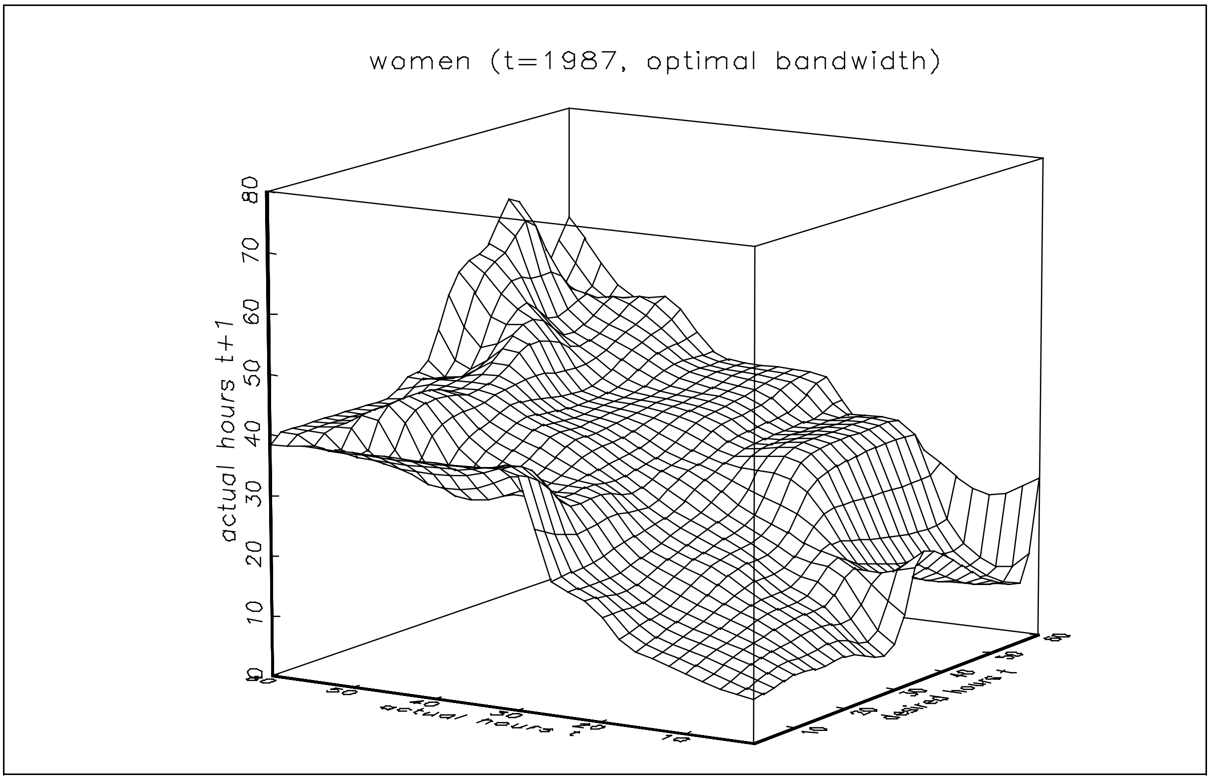


Figure 1b: Nonparametric regression for women, 1987 and 1988



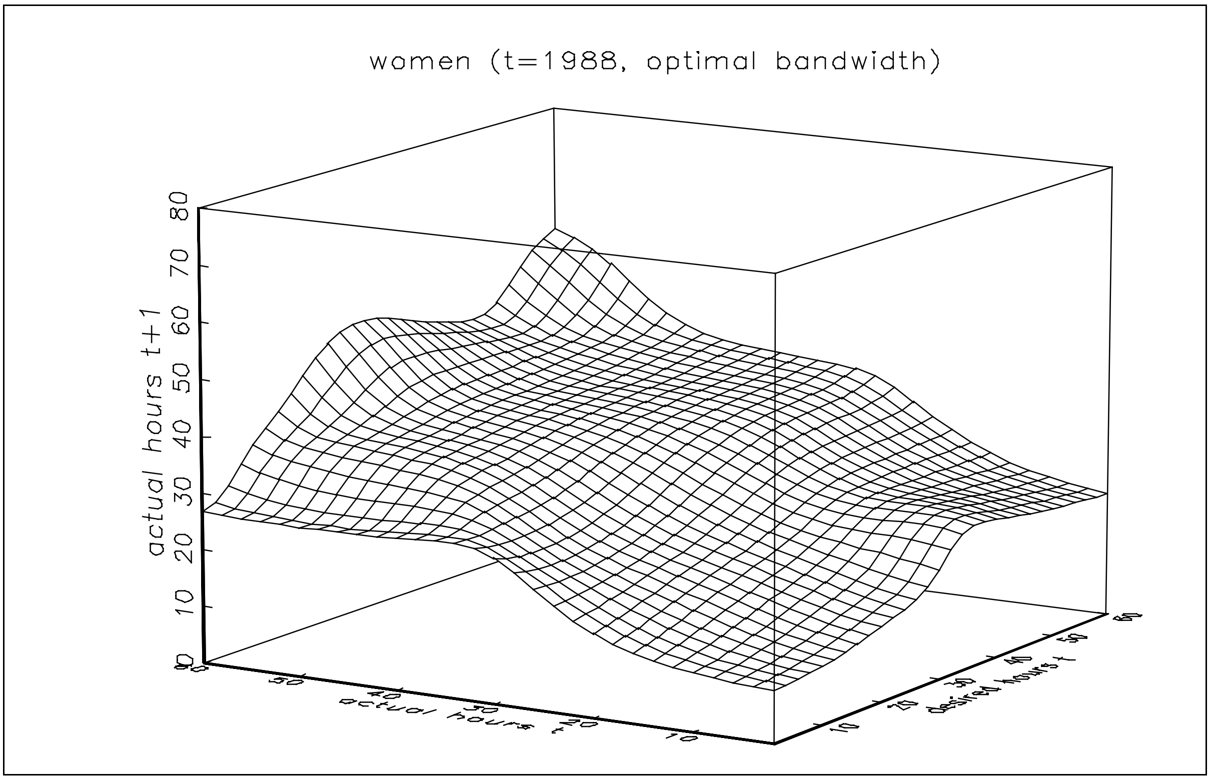


Figure 2a: Uniform confidence bands for men, 1987 and 1988

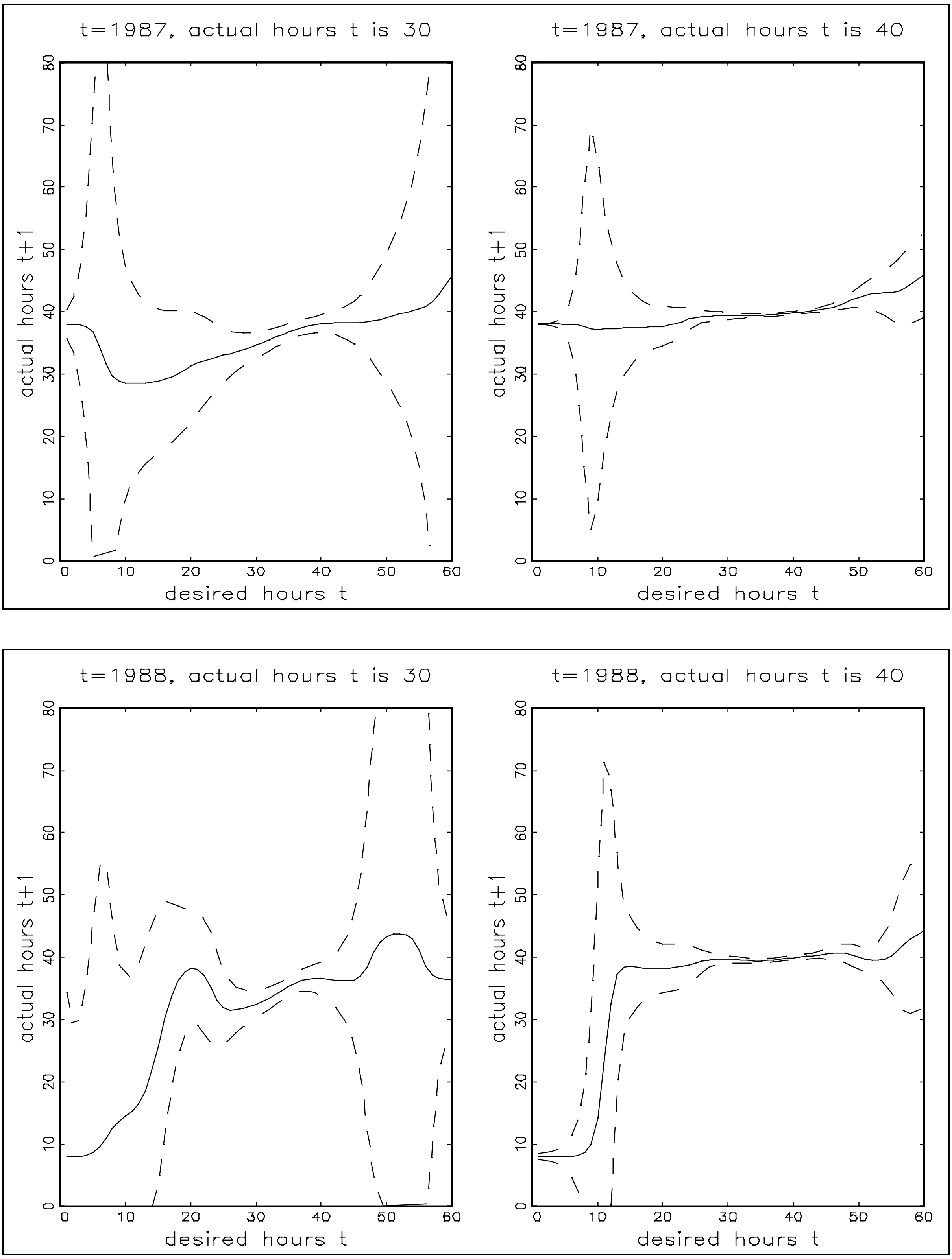
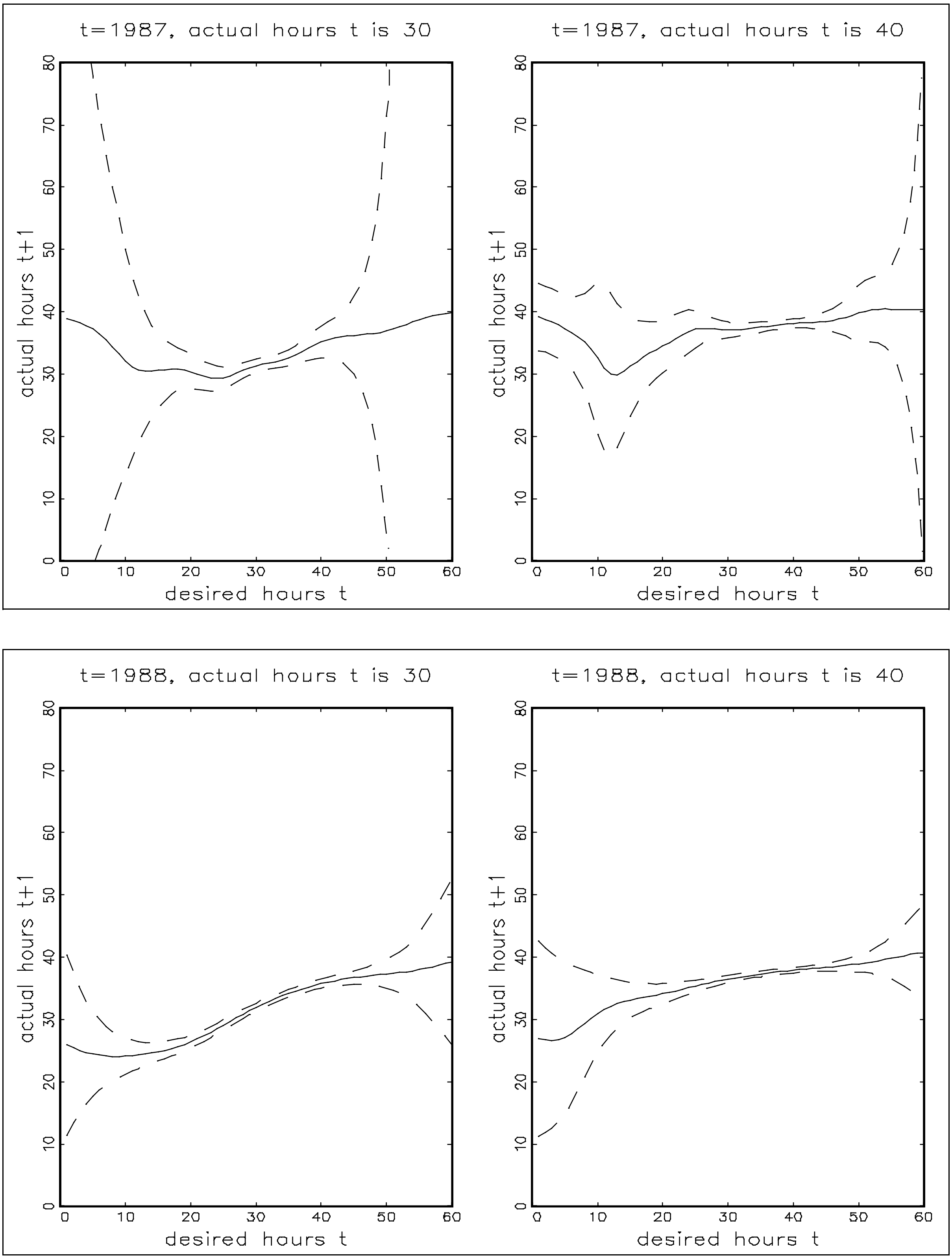


Figure 2b: Uniform confidence band for women, 1987 and 1988



Appendix A: Probability of attrition

Table A.1: sample statistics (working in year t)

	Men		Women	
	t=1987	**t=1988**	**t=1987**	**t=1988**
# observations	3110	3148	1797	1888
one job	96.8%	96.2%	96.5%	95.6%
salaried employment	92.4%	92.8%	92.6%	92.3%
actual hours ha_{it}				
mean	41.32	40.88	26.82	27.05
stand. dev.	10.56	10.63	13.40	13.57
satisfaction s_{it}				
wants to work less	26.6%	23.8%	19.3%	19.1%
satisfied	68.9%	71.9%	71.4%	72.5%
wants to work more	4.5%	4.3%	9.4%	8.5%
desired hours hd_{it}				
mean	39.09	38.95	25.91	26.17
stand. dev.	9.36	9.70	12.07	12.03

Table A.2: probability of being observed at year t+1 for those who work in year t

Men	**t=1987**			**t=1988**		
wants to work:	less	satisfied	more	less	satisfied	more
observed t+1	91.0%	90.7%	90.8%	92.5%	91.4%	89.0%
not observed t+1	9.0%	9.3%	9.2%	7.5%	8.6%	11.0%
# observations	826	2143	141	749	2263	136
LR test	0.077 (prob=0.962)			2.067 (prob=0.356)		

Women	**t=1987**			**t=1988**		
wants to work:	less	satisfied	more	less	satisfied	more
observed t+1	91.0%	91.4%	89.8%	91.7%	89.3%	89.4%
not observed t+1	9.0%	8.6%	10.2%	8.3%	10.8%	10.6%
# observations	346	1283	168	360	1368	160
LR test	0.390 (prob=0.823)			1.909 (prob=0.385)		

Note: The LR test is a likelihood ratio test on independence of row and column events. Under the null hypothesis of independence they follow a χ^2_4 distribution

Table A.3: probit for being observed at next year

Parameter estimate and standard error				
Men	**t=1987**		**t=1988**	
	param.	st.err.	param.	st.err.
intercept	1.738	0.142	1.120	0.131
wants to work less	0.071	0.074	0.063	0.080
wants to work more	-0.092	0.155	-0.050	0.155
more than one job	0.135	0.189	-0.152	0.162
not salaried empl.	0.080	0.130	-0.523	0.115
actual hours ha_{it}	-0.010	0.003	0.007	0.003

Parameter estimate and standard error				
Women	**t=1987**		**t=1988**	
	param.	st.err.	param.	st.err.
intercept	1.482	0.106	1.536	0.099
wants to work less	0.045	0.115	0.281	0.113
wants to work more	-0.136	0.145	-0.114	0.145
more than one job	-0.051	0.224	0.111	0.203
not salaried empl.	0.417	0.194	-0.016	0.146
actual hours ha_{it}	-0.006	0.003	-0.011	0.003

Appendix B: Parametric LM tests, case c

Table B.1: probit for staying employed

Parameter Estimates (P.E.) and corresponding Standard Errors (S.E.)

	MEN				WOMEN			
	1987		1988		1987		1988	
Variable	P.E.	S.E.	P.E.	S.E.	P.E.	S.E.	P.E.	S.E.
intercept	-2.869	0.849	-2.091	0.918	-0.737	0.813	-1.603	0.790
job char.								
#jobs>1	-0.457	0.266	-0.227	0.379	-0.185	0.299	0.157	0.215
not.salaried	-0.894*	0.282	-0.614*	0.293	-0.037	0.173	0.237	0.169
government	0.172	0.139	-0.042	0.122	0.361	0.189	0.110	0.138
ha	0.049*	0.013	0.027*	0.013	0.012	0.013	0.010	0.013
ha.sq/100	-0.049*	0.018	-0.019	0.019	0.009	0.025	0.020	0.025
ind. char.								
age	0.253*	0.037	0.272*	0.038	0.096*	0.035	0.100*	0.035
age.sq/100	-0.344*	0.045	-0.366*	0.045	-0.117*	0.046	-0.119*	0.045
ed.level.2	-0.103	0.148	0.083	0.135	-0.111	0.135	0.026	0.130
ed.level.3	-0.070	0.140	0.318*	0.133	0.114	0.136	0.116	0.128
ed.level.4	0.109	0.198	0.145	0.175	-0.002	0.168	0.177	0.178
ed.level.5	-0.019	0.252	0.315	0.267	0.063	0.370	0.156	0.374
family char.								
single	-0.144	0.202	-0.480*	0.178	0.009	0.154	0.076	0.159
lone.parent	-0.163	0.203	-0.850	0.434	-0.202	0.269	-0.307	0.217
other	-0.519	0.472	-0.173	0.208	0.263	0.179	0.352	0.192
#children	0.028	0.072	-0.072	0.073	0.113	0.070	-0.012	0.063
child<6y	-0.332	0.173	0.291	0.207	-0.505*	0.148	-0.082	0.153
region								
north	0.011	0.198	0.036	0.206	0.117	0.189	0.283	0.180
east	-0.045	0.145	0.249	0.132	-0.058	0.133	0.042	0.122
south	0.106	0.120	0.408*	0.143	-0.013	0.112	0.081	0.129
unemployment	0.009	0.031	0.039	0.041	-0.002	0.029	-0.032	0.038
subj. info.								
dummy less	-0.091	0.191	-0.013	0.213	-0.120	0.194	-0.043	0.208
less*|hd-ha|	0.005	0.016	-0.001	0.019	0.036*	0.015	0.037*	0.018
dummy more	-0.126	0.364	-0.258	0.350	-0.486	0.307	-0.209	0.284
more*|hd-ha|	-0.010	0.026	0.027	0.021	0.015	0.022	0.027	0.018

note: ha gives actual hours and ha.sq/100 gives actual hours squared, divided by 100. The reference group for single, lone parent and other are the married. The dummy other gives the remaining group of single individuals, for instance children older than 16 living with their parents. Child<6y is a dummy for having a child younger than 6 years. Unemployment is the unemployment ratio of the county. Parameters marked with * are significantly different from zero at a five percent significance level.

Table B.2: ordinary least squares for adjustment of working hours

Parameter Estimates (P.E.) and corresponding Standard Errors (S.E.)

	MEN				WOMEN			
	1987		1988		1987		1988	
Variable	P.E.	S.E.	P.E.	S.E.	P.E.	S.E.	P.E.	S.E.
intercept	20.015	4.278	14.123	3.684	11.060	3.440	3.451	3.044
<u>job char.</u>								
#jobs>1	-0.921	1.148	0.187	0.988	2.522*	1.049	1.280	0.883
not.salaried	-3.953*	1.082	-3.657*	0.951	-3.092*	0.742	-0.978	0.719
government	-0.589	0.308	-1.198*	0.264	0.949	0.634	0.231	0.457
ha	-0.317*	0.132	-0.467*	0.121	-0.095	0.053	-0.085	0.045
ha.sq/100	-0.028	0.139	0.191	0.134	-0.216*	0.089	-0.165*	0.076
<u>ind. char.</u>								
age	0.026	0.130	0.292*	0.125	-0.194	0.153	0.081	0.132
age.sq/100	-0.082	0.166	-0.360*	0.157	0.142	0.202	-0.126	0.173
ed.level.2	0.592	0.475	0.211	0.434	-0.065	0.600	-0.349	0.514
ed.level.3	0.744	0.400	-0.176	0.354	0.161	0.579	0.321	0.493
ed.level.4	0.323	0.493	-0.673	0.460	1.709*	0.711	0.302	0.639
ed.level.5	2.072*	0.784	-0.521	0.726	1.572	1.313	2.687*	1.230
<u>family char.</u>								
single	0.350	0.622	0.668	0.605	1.457*	0.716	3.002*	0.665
lone.parent	-0.903	0.637	-0.205	0.486	2.028*	0.620	1.308*	0.543
other	-2.736	1.917	-2.689	2.243	2.303*	1.149	-0.962	0.947
#children	0.240	0.177	0.065	0.148	-0.231	0.280	-0.060	0.250
child<6y	-0.006	0.392	0.293	0.332	-2.382*	0.679	-1.716*	0.603
<u>region</u>								
north	-0.194	0.483	-0.182	0.512	-0.427	0.833	0.271	0.731
east	0.159	0.372	-0.558	0.327	-0.615	0.542	-0.624	0.445
south	-0.042	0.341	0.179	0.370	-0.141	0.475	-0.138	0.482
unemployment	-0.159*	0.079	-0.007	0.107	-0.093	0.125	-0.132	0.146
<u>subj. info.</u>								
dummy less	0.684	0.608	1.128	0.530	0.352	0.844	0.545	0.729
less*|hd-ha|	-0.074	0.068	-0.102	0.066	-0.041	0.071	-0.101	0.064
dummy more	-0.061	1.019	-1.322	1.041	-0.847	1.214	-3.074*	1.185
more*|hd-ha|	0.081	0.108	0.234	0.126	0.230*	0.095	0.568*	0.088

note: ha gives actual hours and ha.sq/100 gives actual hours squared, divided by 100. The reference group for single, lone parent and other are the married. The dummy other gives the remaining group of single individuals, for instance children older than 16 living with their parents. Child<6y is a dummy for having a child younger than 6 years. Unemployment is the unemployment ratio of the county. Parameters marked with * are significantly different from zero at a five percent significance level.

Table B.3: probit for changing job

Parameter Estimates (P.E.) and corresponding Standard Errors (S.E.)

	MEN				**WOMEN**			
	1987		**1988**		**1987**		**1988**	
Variable	P.E.	S.E.	P.E.	S.E.	P.E.	S.E.	P.E.	S.E.
intercept	0.116	0.801	0.922	0.740	2.134	1.053	1.894	0.894
<u>job char.</u>								
#jobs>1	-0.095	0.241	-0.318	0.186	-0.542*	0.260	-0.430*	0.218
not.salaried	0.804*	0.275	0.040	0.180	0.311	0.288	0.471	0.275
government	-0.479*	0.120	-0.560*	0.105	-0.607*	0.237	-0.148	0.137
ha	-0.021	0.014	-0.001	0.013	-0.011	0.018	-0.022	0.014
ha.sq/100	0.014	0.018	-0.006	0.015	0.006	0.033	0.025	0.025
<u>ind. char.</u>								
age	-0.067	0.036	-0.086*	0.034	-0.126*	0.054	-0.123*	0.042
age.sq/100	0.042	0.047	0.056	0.045	0.095	0.079	0.108	0.059
ed.level.2	0.075	0.120	-0.083	0.112	-0.368*	0.176	0.112	0.151
ed.level.3	-0.180	0.116	-0.057	0.102	-0.072	0.163	0.271	0.146
ed.level.4	-0.126	0.154	-0.122	0.146	0.232	0.199	0.340	0.187
ed.level.5	0.042	0.200	0.263	0.169	0.293	0.395	0.499	0.353
<u>family char.</u>								
single	-0.074	0.152	-0.095	0.144	0.109	0.178	0.103	0.165
lone.parent	0.064	0.165	-0.155	0.162	0.131	0.182	0.180	0.151
other	-0.137	0.556	0.431	0.576	0.737*	0.334	0.283	0.272
#children	0.054	0.050	0.101*	0.044	0.025	0.093	0.157*	0.075
child<6	-0.143	0.112	-0.161	0.104	0.035	0.205	-0.313	0.174
<u>region</u>								
north	0.021	0.161	-0.452*	0.166	-0.183	0.258	-0.119	0.209
east	-0.097	0.115	-0.130	0.096	-0.235	0.164	-0.114	0.127
south	-0.013	0.098	-0.084	0.108	-0.099	0.135	-0.166	0.138
unemployment	0.018	0.025	0.056	0.033	-0.006	0.037	-0.041	0.042
<u>subj. info.</u>								
dummy less	-0.009	0.141	0.023	0.134	-0.053	0.262	0.254	0.218
less*|hd-ha|	0.018	0.013	0.011	0.011	0.014	0.023	-0.020	0.023
dummy more	-0.185	0.281	-0.352	0.308	-0.228	0.317	-0.287	0.331
more*|hd-ha|	0.029	0.020	0.043	0.024	0.037	0.023	0.046*	0.022

note: ha gives actual hours and ha.sq/100 gives actual hours squared, divided by 100. The reference group for single, lone parent and other are the married. The dummy other gives the remaining group of single individuals, for instance children older than 16 living with their parents. Child<6y is a dummy for having a child younger than 6 years. Unemployment is the unemployment ratio of the county. Parameters marked with * are significantly different from zero at a five percent significance level.